IMPROVEMENT OF INTERPRETATION OF DISSOLVED GAS ANALYSIS FOR POWER TRANSFORMERS

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Assessment of power transformer conditions and lifespan has acquired crucial significance in latest years. Dissolved Gas Analysis (DGA) has proved to be useful for diagnostic of incipient and potential faults in power transformers. The first part of this paper deals with an experimental investigation carried out to study relation between gas generation and partial discharge. In the second part, a fuzzy logic based interpretation method (FLI), which is founded on fuzzy set theory is described and implemented as an improved DGA interpretation method that provides higher reliability and precision of fault diagnostics.

Key words: PD-Stressing, PRPD, Dissolved Gas Analysis, Fault Detection, Partial Discharge, Fuzzy Logic, Sugeno

1 INTRODUCTION

Transformer population has been approaching the end of its lifespan. Therefore, it has become of vital importance to assess operating conditions of such expensive equipments [2]. Consequently inspections have gained significant importance in order to ensure diagnostic of incipient faults and implementation of necessary maintenance plans to prolong their lifespan.

Technology of oil filled power transformers has remained almost invariable for more than 100 years. Transformer oil and cellulose paper have been utilized as insulating materials, they provide the required dielectric strength and cooling of internal conductors during power transformer operation.

In the case of open-breather transformers, insulating oil is highly prone to undergo changes in its chemical and dielectric properties due to oxidation reactions. The main agents of oxidation are temperature, moisture and oxygen. Reaction accelerators are copper, aluminium and electrical and thermal stresses [9]. Since the transformer oil represents an important information carrier to determine which is the operating condition of a power transformer.

$C_xH_y + O_2 \rightarrow$ *Acids,* H_2O*, Sludge and Gas by-products*

Based on the hydrocarbon nature of mineral transformer oil, oxidation occurs via breakdown of hydrocarbon compounds into small and highly reactive molecules known as free radicals. These process lead to quick chain reactions that combine oxygen to form peroxide radicals in a chain of reactions [1].

Faults in power transformers may occur due to electrical and thermal stresses. These faults can be differentiated for their energy, localization and occurrence period. Along with a fault, there are increased oil temperatures and generation of certain oxidation products such as acids and soluble gases [2].

In the case of electrically induced ageing process due to **p**artial **d**ischarge (PD) phenomena. A PD is a highly localized discharge that may be precursor to a breakdown discharge within the insulation system [6].

The gaseous ageing products dissolved in transformer oil are: hydrogen, methane, ethane, ethylene, acetylene, propane, propene, together with carbon monoxide and carbon dioxide, nitrogen and oxygen.

These gases are considered as fault indicators and can be generated in certain patterns and amounts depending on the characteristics of the fault [2]. Low energy faults leads to formation of hydrogen and saturated hydrocarbon C_1 to C_2, and high energy faults tend to generate unsaturated hydrocarbons C_{2+n} containing double or triple bonds.

Hence, qualitative and quantitative determination of dissolved gases in transformer oil may be of great importance in order to assess fault condition and further operating reliability of power transformers.

2 FAULT GAS ANALYSIS

Through application of the well-known DGA technique, fault gases dissolved in oil can be determined and interpreted. This technique has been successfully employed for many decades [3] as a very effective and rather simple technique to diagnose incipient faults in power transformers.

State of the art online monitoring systems by DGA have become highly advantageous and suitable to detect any abnormal increase of gas concentrations due to any incipient or potential fault developing in a power transformer. Furthermore, continuous monitoring of dissolved gases has been advantageous to study the relationship between gas generation rate and fault.

2.1 INTERPRETATION OF DGA

Several DGA interpretation schemes have been proposed and applied for fault diagnostics [4]. Generally, these interpretation schemes are based on empirical assumptions and practical knowledge gathered by experts all over the world.

Nevertheless, it has been recommended to apply these interpretation schemes with certain precaution since they just provide insights of possible fault diagnostics, however they may also lead to uncertain fault identification [4]. In some cases, DGA interpretation schemes may differ with respect to type and amount of identified faults. That fact is for sure in conflict to a reliable fault diagnostics.

Most of the interpretation schemes are generally based on defined principles such as, gas concentrations, key gases, key gas ratios, and graphical representations. Some of the more applied interpretation schemes are IEC 60599, Key Gas Analysis, Roger and Doernenberg Ratio Methods, Duval Method and Gas Nomograph Method. They are included into the IEEE Standard C57.104-1991.

Since 1990 CIGRE TF 15.01.01 [4] has been revising the different interpretation schemes in order to reconcile some deviations and discrepancies identified among these methods [4]. Hence, by gathering experts' knowledge and incorporating some adjustments, CIGRE proposed a DGA interpretation method that has attempted to improve previous interpretation schemes with the purpose to contribute to more reliable fault diagnostics.

The **C**IGRE **I**nterpretation (CI) scheme consists of a two-step evaluation based on key ratios of gas concentrations and key gas concentrations, both of them compared to thresholds [4]. Therefore, combination of these results indicates fault diagnostics and further necessary actions. For instance, the transformer might be most probably faulty and additional oil analysis is required.

3 GENERATION OF GASES BY PD-STRESSING

3.1 TEST SETUP

The test setup (Fig. 1) was designed using a 12*l* glass tank with open conservator on top, electrode, bare-pressboard-plate and high voltage supply system.

The electrode configuration was used to generate partial discharge on the surface of pressboard. Real time monitoring of PD impulses and voltage supply was done by means of a software application that displays the corresponding **p**hase **r**esolved **p**artial **d**ischarge pattern (PRPD).

The tank was filled with mineral oil SHELL DIALA DX under air saturation and room temperature conditions. Concentrations of dissolved gases were continuously analysed by means of a DGA online-monitoring system throughout conduction of the experiments. The measurement principle of the DGA-OM system is based on gas extraction by a vacuum pump and oil analysis by gas chromatography.

3.2 EXPERIMENTAL CONDUCTION

In order to generate a homogenous and stable PD, preliminary tests were necessary. Thus, the electrode configuration was verified, voltage supply was regulated and initial gas concentrations in oil were determined. Once achieved stable conditions, experiments were carried out throughout certain periods.

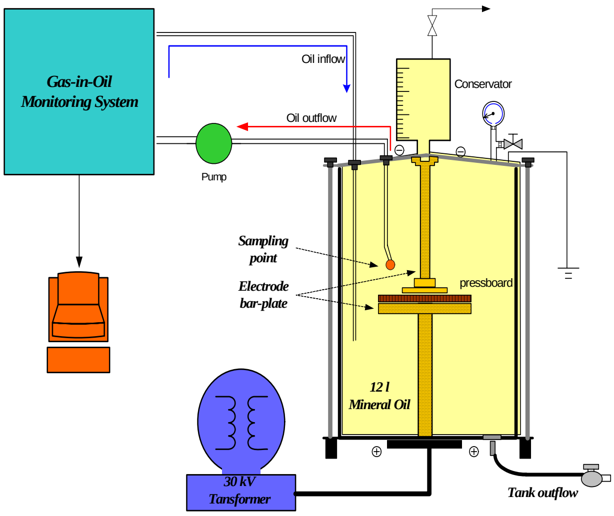

Fig. 1: Test setup for PD-stressing and dissolved gas analysis.

Experiments were performed with PD of 1000 pC. Continuous monitoring of PD-stressing was done by means of observation of displayed PRPD patterns obtained. Two different patterns of PD were identified as shown in Fig. 2 and 4.

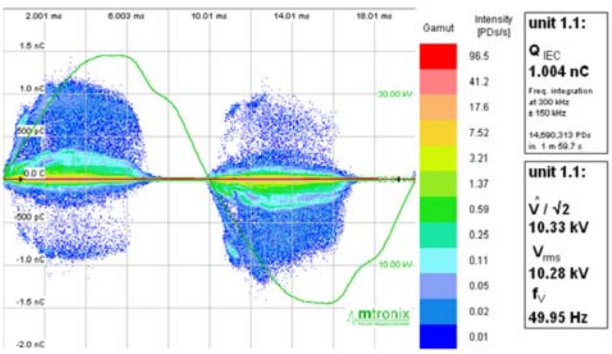

Fig. 2: Phase resolved partial discharge (PRPD) #1.

Fig. 3 shows a significant increase in hydrogen concentration that reached its maximum of 160 ppm at about 50 hours of PD at a voltage of 10.8 kV. Other gas concentrations did not present significant variation. After the point of maximum concentration of hydrogen, concentrations did not presented significant variation, therefore PD was stopped and the decrease of gas concentrations was monitored to verify their rate of diffusion.

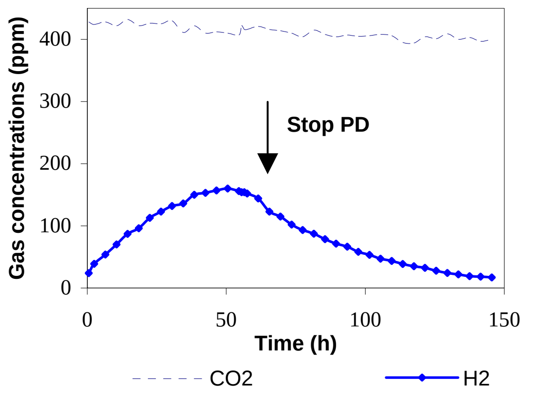

Fig. 3: Variation of gas concentrations for PD #1.

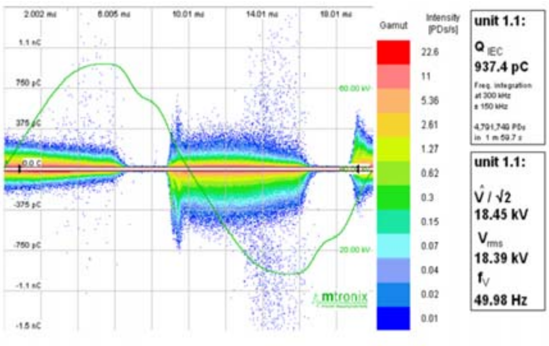

Fig. 4: Phase resolved partial discharge (PRPD) #2.

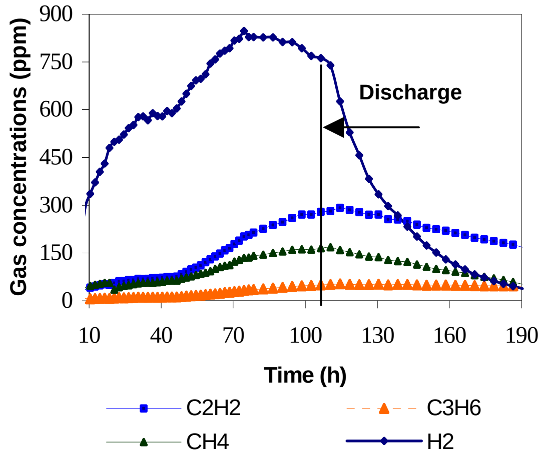

Fig. 5: Variation of gas concentrations for PD #2.

In the case of PD #2 (Fig. 5) can be observed that hydrogen concentrations increased relatively faster to a maximum of 740 ppm within 70 hours of intense PD-stressing at a voltage of 18.4 kV. Among other significant gas concentrations are acetylene, ethylene, and methane. This case presented a strong PD stressing that concluded in a full discharge through the pressboard barrier after 110 hours. During PD stressing gas concentrations increased until a maximum and then started to decrease. After the discharge, monitoring of gases continued to verify their rate of diffusion.

4 DIAGNOSTIC METHOD BASED ON FUZZY INFERENCE SYSTEM (FIS)

The technical condition of a power transformer can be assessed by fault diagnostics based on DGA results. From the mathematical point of view, the problem of fault diagnostics turns out to be the quest for a function, $\vec{f}(\vec{m})$, that maps measurements, $\vec{m}$, to technical conditions, $\vec{c}$. There are at least three fundamental modes for modelling the function $\vec{f}(\vec{m})$:

1. If the physical relations between measurements and technical conditions can be mathematically described, then it is possible to find an analytical solution for $\vec{f}(\vec{m})$.
2. If the physical relations between measurements and technical conditions cannot be described at all, but there is information available to describe $\vec{f}(\vec{m})$ in a linguistic manner [7], then a solution based on a **f**uzzy **i**nference **s**ystem (FIS) is possible.
3. If the physical relations between measurements and technical conditions cannot be described at all, but data that describes $\vec{f}(\vec{m})$ for some supporting points is available, then a neural network can be trained with these supporting points. The neural network can abstract from these supporting points and thereby make estimation of $\vec{f}(\vec{m})$.

Mode 2 was selected to improve the Cigre interpretation (CI). The use of a Fuzzy Inference System (FIS) as a tool could already eliminate some deficiencies of CI on the basis of the following statements:

- CI describes two methods that use two key criteria for fault detection. The new approach uses two key criteria as well, but they have been well integrated into one single method.
- CI uses thresholds to decide whether a transformer is faulty or not. That can lead to wrong interpretation, especially in case of values close to the thresholds. This new approach eliminates

thresholds and uses steady membership functions instead.

- CI attempt to define the type of fault that might be taking place. The new approach estimates the likelihood of fault occurrence for each possible fault type.

4.1 BASICS OF FUZZY-INFERENCE-SYSTEM (FIS)

There are different classes of fuzzy logic but all of them are based on fuzzy set theory [10]. Fuzzy sets differ to binary sets in the number of feasible membership values. While for binary sets two membership values, $\{0,1\}$, are defined, fuzzy sets additionally use pseudo-membership values, $]0,1[$.

For the class of fuzzy logic that has been proposed by Mamdani or Sugeno, production rules map fuzzy sets to other fuzzy sets. Production rules are a pre-condition for qualitative modelling [8] by FIS. Qualitative modelling with FIS (Fig. 6) is based on three main steps of mapping.

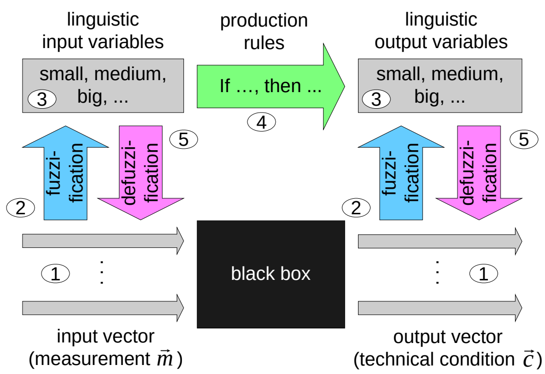

Fig. 6: Transformation by means of a FIS subdivided in main steps.

The first step is known as fuzzification (Fig. 6-2). In this step a physical problem is transformed into a linguistic problem. For this purpose both the input vector and the output vector (Fig. 6-1) are mapped to linguistic variables (input variables and output variables, respectively, Fig. 6-3) by means of membership functions of type $\mu : \Re \to [0,1]$.

Within the second step, called inference, production rules (Fig. 6-4) adjust the mapping of the output vector to the linguistic output variables based on the mapping of the input vector to the linguistic input variables. Each rule can conjunctively or disjunctively combine two or more premises (membership value of an input value to a linguistic input variable). Furthermore, production rules can be weighted depending on how reliable they are. Thus, the linguistic problem can be solved.

The last step is to perform defuzzification (Fig. 6-5). That means the already solved linguistic problem will be converted into a physical problem that is also solved.

Mamdani and Sugeno type fuzzy logic differ fundamentally in steps ‘inference’ and ‘defuzzification’.

4.2 NEW FUZZY LOGIC INTERPRETATION (FLI) BASED ON FIS

One deficiency of CI that has already been mentioned ahead is the usage of two independent interpretation methods for fault detection. One of these methods depends on key gases, the other on key gas ratios.

By contrast, fuzzy logic interpretation (FLI) can incorporate both of those methods in a single method that can consider both criteria (key gas concentrations and key gas ratios) simultaneously for each fault type. Only, the fault ‘tank tap changer’ [4] depends on single criteria. The major outcome of this integration is an improved interpretation and therefore a more reliable fault diagnostics.

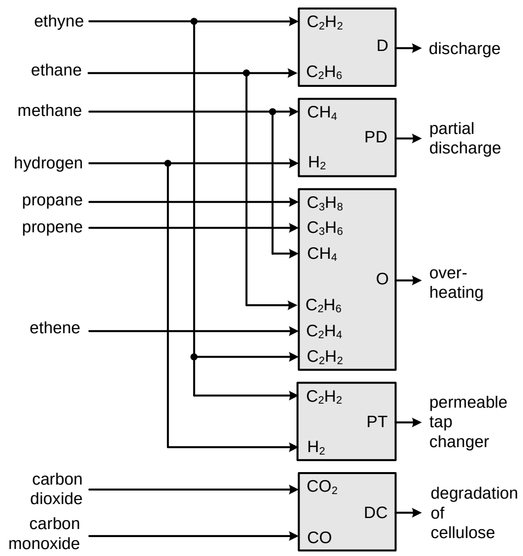

Fig. 7: Considered measurements per type of fault.

Starting from the gas concentrations obtained by gas-in-oil analysis, (Fig. 7), ratios of gas concentrations have to be derived from these gas concentrations. Gas concentrations and ratios of gas concentrations that are decisive for a particular type of fault are called key gases and key gas ratios, respectively. The Fig. 8 represents relevant key gases and key gas ratios to detect partial discharge.

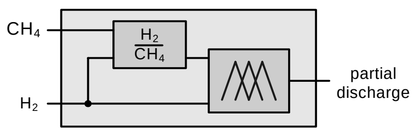

Fig. 8: Relevant key gases and key gas ratios to detect partial discharge.

In the following, the zero-order Sugeno type FIS that is used in FLI is explained in more detail.

Partial discharge has been used as an example. The proceeding for other fault types is done in analogical way.

4.3 FUZZIFICATION

FIS integrates two 1-dimensional domains from CI, namely key gas hydrogen (H) and key gas ratio hydrogen/methane (HM), in one single 2-dimensional domain as represented in Fig. 9.

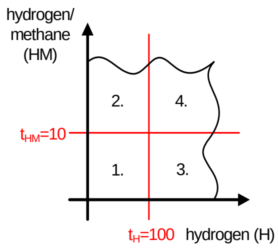

Fig. 9: Combination of two 1-dimensional domains to a 2-dimensional domain.

For each threshold, t_x, with $x \in \{HM, H\}$, FIS places a pair of sigmoid membership functions in accordance to equation (1) and (2). Parameter b in these equations is set to t_x, thus constraint $\mu_{\mathrm{b}}(a,b;x=\mathrm{t}_x)=\mu_{\mathrm{s}}(a,b;x=\mathrm{t}_x)=0,5$ is fulfilled.

$$\mu_{\mathrm{b}}(a,b;x)=\frac{1}{1+e^{-a(x-b)}}, a \in \Re \qquad (1)$$

$$\mu_{\mathrm{s}}(a,b;x)=1-\mu_{\mathrm{b}}(a,b;x) \qquad (2)$$

Sigmoid membership functions are steady. This property is an inevitable pre-condition for a FIS.

For the image set 'partial discharge' (PD) FIS uses singleton membership functions accordant to equation (3). For each $i \in \{\mathrm{vu,u,l,vl}\}$ a membership function $\mu_i(c;PD)$ maps a likelihood value c for PD to a corresponding singleton.

$$\mu_i(c;PD)=\begin{cases}1, \text{ if } \mathrm{PD}=c \\ 0, \text{ else}\end{cases} \qquad (3)$$

Singletons are typical for zero-order Sugeno type fuzzy inference. They make defuzzification much easier and faster then in Mamdani type fuzzy inference.

Value	Linguistic variable	Membership function	Parameterization
H	small	$\mu_{\mathrm{s}}(a,b;H)$	$(a,b)=(0.08,100)$
	big	$\mu_{\mathrm{b}}(a,b;H)$	
HM	small	$\mu_{\mathrm{s}}(a,b;HM)$	$(a,b)=(0.8,10)$
	big	$\mu_{\mathrm{b}}(a,b;HM)$	
PD	very **u**nlikely	$\mu_{\mathrm{vu}}(c;PD)$	$c=0$
	unlikely	$\mu_{\mathrm{u}}(c;PD)$	$c=33$
	likely	$\mu_{\mathrm{l}}(c;PD)$	$c=66$
	very **l**ikely	$\mu_{\mathrm{vl}}(c;PD)$	$c=100$

Tab. 1: Membership functions and parameterization to detect partial discharge.

Tab. 1 shows for each value linguistic variables and corresponding membership functions with their parameterization. The settings '0' and '100' for parameter c are a direct outcome of CI, but settings '33' and '66' are estimations. Estimations were done based on the significance of the production rule.

4.4 INFERENCE

As Fig. 9 shows, the domain is subdivided into 4 areas by thresholds t_{HM} and t_{H}. Each area corresponds to a linguistic area as follows [11]:

1. $(H<t_{\mathrm{H}}, HM<t_{\mathrm{HM}}) \leftrightarrow (\mu_{\mathrm{s}}(H)>0.5, \mu_{\mathrm{s}}(HM)>0.5)$
2. $(H<t_{\mathrm{H}}, HM \geq t_{\mathrm{HM}}) \leftrightarrow (\mu_{\mathrm{s}}(H)>0.5, \mu_{\mathrm{b}}(HM)\geq 0.5)$
3. $(H \geq t_{\mathrm{H}}, HM<t_{\mathrm{HM}}) \leftrightarrow (\mu_{\mathrm{b}}(H)\geq 0.5, \mu_{\mathrm{s}}(HM)>0.5)$
4. $(H \geq t_{\mathrm{H}}, HM \geq t_{\mathrm{HM}}) \leftrightarrow (\mu_{\mathrm{b}}(H)\geq 0.5, \mu_{\mathrm{b}}(HM)\geq 0.5)$

For each linguistic area, exactly one production rule conjunctively combines $\mu_i(HM)$ and $\mu_j(H)$ with $i, j \in \{\mathrm{b,s}\}$ in its premise. Membership functions can be regarded as probability density functions; hence it is reasonable to define the conjunctive combination as multiplication as in equation (4).

$$\begin{aligned}&\forall j \in \{vl,l,u,vu\}\ \exists k \otimes l \in \{\mathrm{b,s}\} \otimes \{\mathrm{b,s}\}: \\ &w_j = AND(\mu_k(H), \mu_l(HM)) = \mu_k(H) \cdot \mu_l(HM)\end{aligned} \qquad (4)$$

The conclusion is done through scaling of the likelihood value PD for that μ_j is 1, like in equation (5).

$$\forall j \in \{vl,l,u,vu\}: s_j = w_j \cdot PD|_{\mu_j=1} \qquad (5)$$

Additional to the mathematical description of the inference, the Tab. 2 shows the inference in a verbal representation through production rules. All four production rules are weighted equally with ¼, that means they have equal importance.

Production rule	Weight
If H is **big** and HM is **big**, then PD is **very likely**	$\frac{1}{4}$
If H is **big** and HM is **small**, then PD is **unlikely**	$\frac{1}{4}$
If H is **small** and HM is **big**, then PD is **likely**	$\frac{1}{4}$
If H is **small** and HM is **small**, then PD is **very unlikely**	$\frac{1}{4}$

Tab. 2: Production rules that are used to detect PD.

4.5 DEFUZZIFICATION

The estimated likelihood of partial discharge in percent is the so-called weighted average as in equation (6).

$$PD\ [\%] = \frac{\sum_{j\in\{vl,l,u,vu\}} s_j}{\sum_{j\in\{vl,l,u,vu\}} w_j} \tag{6}$$

5 COMPARISON BETWEEN CI AND FLI

The in-house software TRAFADETO – **Tr**ansformer **Fa**ult **De**tection **To**ol, has been developed to implement the new fuzzy logic interpretation method (FLI). This software was applied to compare CI and FLI by means of the results obtained from above mentioned experimental measurements.

For application of this software maximum gas concentrations obtained from conduction of experiments of gas generation by PD-stressing (Fig. 3 and 5) were used as a measurement vector, see Tab. 3.

		PD #1	PD #2
Gases (ppm)	**CO**	3.7	14
	CO_2	410	434
	H_2	152	847
	CH_4	9.1	135
	C_2H_6	2.3	43.9
	C_2H_4	1.8	105
	C_2H_2	3.3	202
	C_3H_8	0.7	11
	C_3H_6	1.6	33

Tab. 3: Measurement vectors with maximum hydrogen.

Interpretation of DGA by CI resulted in the diagnostics of following faults: **d**ischarge (D), **p**artial **d**ischarge (PD), **o**verheating (O)**, p**ermeable tank **t**ap changer (PT) and **d**egradation of **c**ellulose (DC)**.** As one can see in Tab. 4, key gas and key gas ratio method from CI resulted in uncertain diagnostic of faults. For instance, in case of for PD #2, the key gas method identifies D and PD as faults, whereas key gas ratio method identifies D, O and DC as faults.

Key gas method		Estimated faults	Key gas ratio method	
PD #1	**PD #2**		**PD #1**	**PD #2**
No	Yes	**D**	No	Yes
Yes	Yes	**PD**	Yes	No
No	No	**O**	No	Yes
---	---	**PT**	No	No
No	No	**DC**	Yes	Yes

Tab. 4: Estimated faults by key gas method and key gas ratio method of CI.

By contrast, Tab. 5 shows the results of interpretation of DGA by FLI. In case of PD #1 the FLI estimated PD as the most likely fault. Nevertheless, 60% likelihood of DC suggests that the pressboard plate in between the bare-plate electrode system could have been affected. In case of PD #2 the FLI estimates D and O as most likely faults. That might be due occurrence of a strong PD and discharge. Furthermore, PD #1 suggested a likelihood of 60 % DC that may indicate effect of pressboard. The likelihood of 36.2% PD indicates the strong PD-stressing prior to the discharge. The likelihood of 99.9% for overheating was inconsistent and therefore suggests that this model should be further improved. Future work will focus on that point.

		PD #1	PD #2
Estimated Likelihood of fault [%]	**D**	58.3	100.0
	PD	99.2	36.2
	O	9.0	99.9
	PT	0.0	0.1
	DC	60.0	60.0

Tab. 5: Estimation of fault likelihood by FLI.

6 SUMMARY

Gas generation due to partial discharges was investigated in a laboratory scale setup by means of an on-line monitoring system based on gas chromatography. Experimental results demonstrated that type and rate of gas generation depend on the intensity of PD stressing.

A new DGA interpretation method based on fuzzy logic (FLI) was developed using the well-known Cigre interpretation rules. This novel method attempts to overcome some deficiencies derived from conventional application of the Cigre interpretation (CI) method. Thus, by means of estimation of fault occurrence likelihood, it is possible to provide a more reliable as well as precise fault diagnostics in power transformers.

The comparison of conventional and fuzzy logic interpretation by means of results obtained from experimental measurements showed the advantage of the new method in terms of reliability of the DGA interpretation result. Ongoing experiments of gas generation by PD will contribute to enlarge analytical knowledge related to gas generation processes and provide additional rules for the new method.

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